Dear Editor and Reviewers,

We sincerely thank you for the time and effort you have devoted to reviewing our manuscript, as well as for the constructive and insightful comments, which have been essential in guiding a substantial revision of this work. In response to the concerns raised in the previous round, we have undertaken a comprehensive and thorough revision of the manuscript, in which both the overall structure and the core content have been extensively reworked rather than lightly edited.

In particular, the analytical framework has been reorganized, the modeling strategy has been clarified, the methodological descriptions have been substantially expanded, and the interpretation of the results has been strengthened and made more consistent with the underlying physical processes. These revisions were carried out with the aim of improving not only clarity, but also the scientific rigor and logical coherence of the study as a whole.

All changes have been clearly indicated in the revised manuscript for ease of reference. In the following, we provide a detailed, point-by-point response to each comment, in which the reviewers' comments are presented in italics and our responses are given directly below.

Comment 1: Although Figure 2 presents a workflow, the overall modeling chain is still not sufficiently clear. In particular, the relationship between the SWAT model and the LightGBM model is not easy to follow. The authors should explain more explicitly what the exact inputs and outputs of each model are, how the two models are linked, and how this modeling framework is finally used to attribute the effects of dam regulation.

We thank the reviewer for the constructive comment. We acknowledge that the description of the modeling workflow in the original manuscript was not sufficiently clear, particularly with regard to the relationship between the SWAT and LightGBM models, which may have led to misunderstanding of the modeling strategy. We sincerely apologize for this lack of clarity.

In fact, this study adopts a sequential modeling framework rather than a coupled model. Different models are used to represent basin-scale drivers and lake response processes separately, and are then combined to enable a quantitative decomposition of multi-scale influences. This concept has now been clarified and elaborated in the revised manuscript, as detailed below. The primary objective of this study is to address the following question: how to quantitatively separate the effects of basin inflow and mainstream hydrodynamics on discharge at Hukou, given that it is jointly controlled by both factors.

First, a baseline relationship describing the natural response of discharge at Hukou is established. Using observations from normal-flow conditions, a LightGBM-based discharge response model is developed to represent the behavior of the lake system under weak mainstream interference. This model captures the mapping between inflow from the five tributaries and discharge at Hukou, and thus reflects the intrinsic relationship governing the transformation of basin inflow into lake outflow in the absence of strong backwater effects.

Based on this baseline, the influence of mainstream backwater during backflow events is quantified. Specifically, the observed inflow from the five tributaries during backflow events is input into the response model to reconstruct the corresponding discharge at Hukou under the assumption of no strong mainstream interference. The difference between the reconstructed discharge and the observed discharge during the same period is then interpreted as the effect of backflow and mainstream forcing, which allows a direct estimation of the contribution of backflow processes.

The SWAT model in this study is used primarily to analyze the mechanisms of basin inflow variation. By setting different land use and climate scenarios, SWAT is used to simulate basin inflow processes under multiple conditions, which provides the basis for examining how changes in basin runoff influence the hydrological response at Hukou. Therefore, the SWAT model is not directly involved in the quantification of backflow effects, but serves as a tool to characterize basin-scale drivers and to explore how variations in inflow regulate the hydrodynamic response of the lake system under different scenarios.

The corresponding revisions have been incorporated into the manuscript at 169-209：

2.4 Basin Inflow Simulation and Quantification of Influencing Factors

To establish a unified reference for analyzing hydrological processes in the lake and to separate the effects of basin inflow from those of mainstream hydrodynamics, a sequential modeling framework is constructed, which consists of a Hukou discharge response model and a basin inflow simulation model.

(1) Hukou Discharge Response Model

In order to characterize the natural response of the lake system to basin inflow under conditions of weak mainstream influence, a Hukou discharge response model is developed using the LightGBM machine learning approach. Training data are selected from normal-flow hydrological conditions during which hydrodynamic conditions are relatively stable, the influence of the Yangtze River mainstream is weak, and no backflow occurs. Based on daily observations of inflow from the five tributaries and outflow at Hukou, a mapping relationship is established in which discharge at Hukou is controlled solely by basin inflow.

The model is trained and tested using a time series split in which 80% of the data are used for training and 20% for testing. Model performance is optimized by adjusting the number of trees, learning rate, and sampling parameters, while early stopping is introduced to prevent overfitting. In addition, segmented modeling is conducted using 2003 as a breakpoint in order to capture stage-dependent variations in the discharge response relationship. Model performance is evaluated using percentage bias (PBIAS), root mean square error (RMSE), and Nash–Sutcliffe efficiency (NSE).

After model validation, two types of applications are conducted. First, observed inflow from the five tributaries during backflow events is used as model input to reconstruct the discharge process at Hukou under the assumption of no strong mainstream influence, and the reconstructed discharge is compared with observed discharge in order to quantify the contribution of backflow effects. Second, basin inflow under different scenarios is input into the model to reconstruct discharge at Hukou under a unified reference condition, which enables comparison of hydrological processes across different scenarios.

(2) Basin Inflow Simulation Using SWAT

To quantitatively attribute the mechanisms through which basin hydrological changes influence discharge at Hukou, the SWAT model is used to generate basin inflow series under multiple scenarios, which allows assessment of how variations in basin runoff regulate hydrodynamic responses at Hukou. During model calibration and sensitivity analysis, key parameters are selected and optimized, including those at the basin scale, HRU scale, soil properties, groundwater processes, and channel characteristics. Model parameters are iteratively adjusted to ensure good agreement between simulated and observed discharge.

Since the period from 1990 to 2010 represents the most significant stage of land use change in the Poyang Lake basin, while changes become relatively stable after 2010, the years 1990 and 2010 are selected as representative scenarios for comparison. After calibration, meteorological and land use data under different scenarios are input into the model to simulate basin inflow processes, which serve as the basis for discharge simulation at Hukou.

It should be noted that SWAT produces monthly runoff series for the five tributaries, whereas the Hukou discharge response model is constructed at a daily scale. To ensure consistency between the two models, monthly runoff is uniformly distributed according to the number of days in each month under the constraint of mass conservation, thereby converting it into daily inflow series for use as model input. Although this approach may smooth short-term fluctuations at the daily scale, the primary objective of this study is to analyse relative changes and stage-dependent characteristics under different scenarios rather than to reproduce daily extremes, and therefore the impact of this temporal transformation on the results is limited.

Comment 2:

The performance of the hydrological model needs to be presented more comprehensively. At present, the manuscript mainly reports R^2 values for SWAT, but R^2 alone is not sufficient to demonstrate good simulation performance. For example, even if simulated values are systematically biased, R^2 may still be high. I suggest that the authors provide additional performance metrics such as NSE, KGE, PBIAS, and/or hydrograph comparisons. In addition, except for the Ganjiang River, the reported R^2 values for the other tributaries are only moderate (e.g., 0.64, 0.67, 0.66, and 0.60). The authors should discuss how the uncertainty in tributary runoff simulation may propagate into the subsequent simulation of Hukou discharge and eventually affect the conclusions regarding lake hydrological regime shifts.

We thank the reviewer for the insightful comments regarding model uncertainty. We agree that the simulation accuracy of tributary runoff using the SWAT model is not optimal. Although, except for the Ganjiang River, the R^2 values of the other tributaries are generally at a moderate level, the overall model performance, when evaluated together with the NSE metric, is still able to reasonably capture both the variability and magnitude of basin runoff. In particular, the simulated results show good agreement with observations in terms of temporal trends and stage-dependent fluctuations, which is sufficient for representing the basin inflow signals required for subsequent analysis.

It should also be emphasized that, within the modeling framework, SWAT simulations are primarily used to explore the pathways through which basin inflow variations influence the hydrological response at Hukou under different scenarios. The attribution of the key drivers of discharge at Hukou does not directly rely on SWAT-simulated values, but is instead based on the response relationship established using observed inflow and the LightGBM model. Therefore, although the SWAT simulations are of moderate accuracy, they are adequate for capturing the temporal patterns and stage-dependent characteristics of basin inflow, and the associated uncertainties are not directly propagated into the quantitative estimation of backflow effects, resulting in a limited impact on the main conclusions.

Furthermore, it should be noted that discharge at Hukou is jointly controlled by basin inflow and mainstream hydrodynamics. Under backflow conditions and strong backwater effects, the influence of mainstream hydrodynamics becomes dominant, while the relative contribution of basin inflow is reduced. As a result, even if uncertainties exist in tributary runoff simulations, their influence on identifying the dominant control mechanisms of discharge at Hukou remains limited.

In summary, although uncertainties exist in the simulation of tributary runoff, their impact on the key conclusions of this study remains limited, in that discharge at Hukou is primarily regulated by mainstream hydrodynamics and exhibits a clear stage-dependent transition.

The corresponding revisions have been incorporated into the manuscript at 489-513:

4.3 Limitations and Implications for Future Management

This study develops an integrated analytical framework that combines observational data, machine learning, and hydrological modeling to quantify the evolution of hydrological conditions in Poyang Lake under the influence of the Three Gorges Project. The approach can be regarded as an observation-driven counterfactual framework, in which a reference condition without mainstream interference is constructed to quantify deviations in the actual system, thereby indirectly identifying the influence of mainstream hydrodynamics. Based on this framework, a set of evaluation indicators is established to systematically analyze lake regulation mechanisms under different hydrological conditions from the perspectives of basin inflow and mainstream constraints. The discharge response model constructed under normal-flow conditions shows high accuracy under baseline conditions, and the deviations identified in typical events exhibit consistent directionality and physical plausibility, which indicates that the method is capable of capturing system responses and provides a feasible approach for mechanism identification under complex river–lake interaction conditions where high-resolution hydrodynamic boundary data are unavailable.

Despite these advantages, several sources of uncertainty should be acknowledged. First, basin inflow simulation is based on the SWAT model, and differences in simulation accuracy among tributaries may introduce uncertainty in the magnitude of inflow. However, since this study focuses on relative changes and stage-dependent characteristics, the influence of this uncertainty on the overall conclusions is limited. Second, the discharge response model is constructed based on normal-flow conditions, and its application to backflow and low-flow events may introduce some extrapolation error. Nevertheless, the model shows high accuracy under baseline conditions, and the identified deviations exhibit consistent directional behavior in typical events, which suggests that the results primarily reflect systematic responses rather than random error. In terms of attribution, the counterfactual framework identifies the influence of mainstream hydrodynamics through systematic deviations between theoretical and observed discharge, which provides a degree of robustness against random uncertainty. Although these uncertainties may affect specific numerical estimates, they have limited influence on the qualitative conclusions regarding the restructuring of hydrological regimes and their driving mechanisms.

Comment 3:

Figure 6 needs clarification. Please clearly explain what the color scale represents (for example, whether it represents the number of events) and why the blue points, which seem to indicate backflow events, are different among the panels. At present, this figure is not easy to interpret.

We thank the reviewer for the valuable comments on Figure 6. In response to the suggestions, the figure has been comprehensively revised in order to improve its readability and clarity of presentation. The specific modifications are shown in the revised figure below. Through these revisions, Figure 6 is now able to more clearly illustrate the spatiotemporal distribution of different hydrological conditions, as well as the variation patterns of backflow events. The corresponding content has been updated in the revised manuscript.

The specific revisions can be found in Lines 273–274.

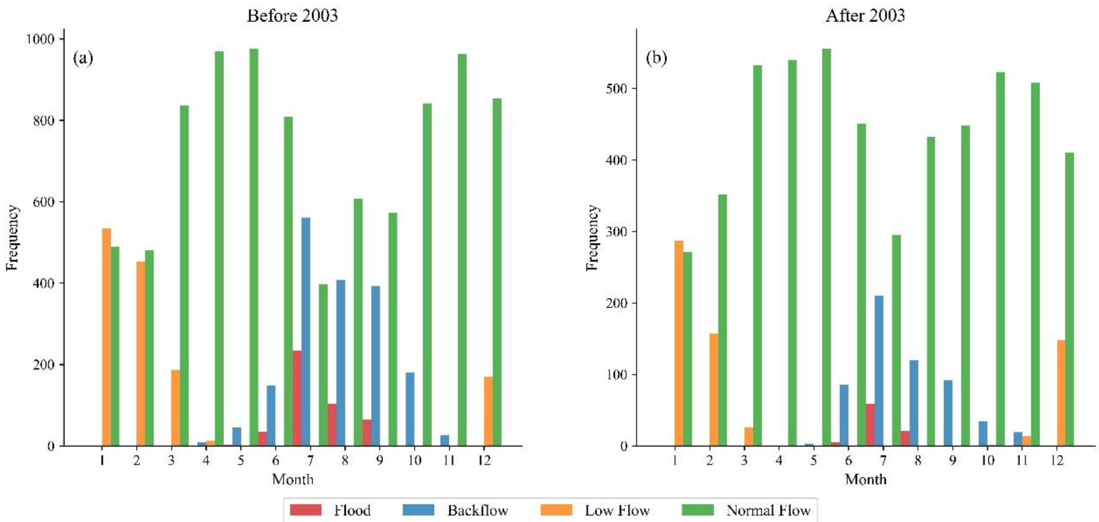

Figure 4 Intra-annual Distribution Characteristics of Different Hydrological Events

Comment 4:

I am not fully convinced by the interpretation of Figures 8 and 9. These figures compare simulated/theoretical discharge with observed discharge under backflow and drought conditions. However, if the baseline model is established under normal-flow conditions, then the discrepancy between simulated and observed values may also reflect model structural error or extrapolation error, rather than reservoir impact itself. The manuscript needs to better justify why these differences can be interpreted as evidence of reservoir influence or increased hydraulic resistance, instead of simply representing model error characteristics.

We thank the reviewer for raising this important point. We agree that, when a model trained under normal-flow conditions is extrapolated to backflow or low-water scenarios, the differences between simulated and observed values may include components of model error. Accordingly, in the revised manuscript, we have further clarified the physical meaning of this difference and strengthened its interpretation.

It should first be emphasized that the difference between simulated and observed discharge is not treated as a simple model error nor directly attributed to reservoir regulation. Instead, it is defined as a physically interpretable metric, namely the outflow resistance index (BI), which is expressed as:

$$BI = Q_{pred} - Q_{obs}$$

where Q_{pred} represents the reconstructed discharge under the assumption of no strong mainstream interference based on the observation-driven model, while Q_{obs} denotes the observed discharge. Therefore, BI characterizes the deviation of the actual system from the "natural response state" and can be interpreted as the strength of external hydrodynamic constraints, such as mainstream backwater effects and backflow processes, rather than as a mere model residual.

Furthermore, in order to reduce the potential influence of random errors associated with differences at individual time steps, the analysis is not based solely on BI itself, but instead on the relationship between BI and inflow from the five tributaries (Q_{wuhe}), which is expressed as:

$$BI = a + S \cdot Q_{wuhe}$$

where S denotes the resistance sensitivity at Hukou, which describes how variations in basin inflow influence outflow resistance. By establishing this relationship, systematic deviation characteristics are extracted at the statistical level, thereby reducing the influence of random model errors on the interpretation of results.

In addition, in terms of model performance, the LightGBM model shows high accuracy under the baseline (normal-flow) conditions, with NSE values of approximately 0.94 before and after 2003, PBIAS close to zero, and stable RMSE values, which indicates that the model is able to reliably represent the natural response relationship between basin inflow and discharge at Hukou. Under this well-defined baseline, the systematic deviations identified are therefore more likely to reflect external hydrodynamic processes that are not explicitly represented in the model, rather than deficiencies in model structure.

At the same time, it is observed that BI exhibits a pronounced positive bias during backflow events, as Q_{pred} is systematically higher than Q_{obs}, and this deviation shows clear temporal clustering and directional consistency, which is highly consistent with the physical mechanism whereby mainstream backwater suppresses outflow at Hukou. This consistency suggests that the observed differences are not only numerical but also physically meaningful.

Based on the above analysis, the differences are not interpreted as simple model errors, but rather, from the perspective of deviations from a counterfactual baseline, are used to quantify the influence of mainstream hydrodynamic processes on discharge at Hukou. The corresponding explanations have been further clarified and strengthened in the revised manuscript.

The specific revisions can be found in Lines 210-231 and 501-512：

210-231：

2.5 Indicators of Lake Regulation and Outflow Response

To comprehensively characterize lake storage–regulation processes and outflow response at Hukou, an indicator system is established that includes water storage intensity and outflow resistance, which together represent both water balance conditions and hydrodynamic constraints.

First, a storage intensity index (SI) is introduced to describe the water balance status of the lake:

$$SI = \frac{Q_{\text{out}} - Q_{\text{in}}}{Q_{\text{in}}}$$

Q_{in} and Q_{out} represent total inflow and total outflow, respectively. When $SI > 0$ is greater than zero, the lake is dominated by outflow, whereas when $SI < 0$, water storage or outflow obstruction dominates.

Furthermore, in order to quantify the influence of external hydrodynamic forcing on outflow processes at Hukou, an outflow resistance index (BI) is defined as

$$BI = Q_{pred} - Q_{obs}$$

Where Q_{pred} represents the theoretical outflow under conditions without mainstream interference, and Q_{obs} represents the observed outflow. When BI >0, outflow at Hukou is inhibited, whereas when BI <0, outflow is enhanced.

On this basis, a linear relationship between outflow resistance and basin inflow is established by taking inflow from the five tributaries as the independent variable, which can be expressed as

$$BI = a + S \cdot Q_{wuhe}$$

where S denotes the resistance sensitivity coefficient at Hukou, which characterizes the response of outflow resistance to variations in basin inflow.

Through this indicator system, lake regulation processes and their driving mechanisms under different hydrological conditions can be systematically analyzed from two perspectives, which include overall water balance represented by SI and local hydrodynamic constraints represented by BI and S.

501-512：

Despite these advantages, several sources of uncertainty should be acknowledged. First, basin inflow simulation is based on the SWAT model, and differences in simulation accuracy among tributaries may introduce uncertainty in the magnitude of inflow. However, since this study focuses on relative changes and stage-dependent characteristics, the influence of this uncertainty on the overall conclusions is limited. Second, the discharge response model is constructed based on normal-flow conditions, and its application to backflow and low-flow events may introduce some extrapolation error. Nevertheless, the model shows high accuracy under baseline conditions, and the identified deviations exhibit consistent directional behavior in typical events, which suggests that the results primarily reflect systematic responses rather than random error. In terms of attribution, the counterfactual framework identifies the influence of mainstream hydrodynamics through systematic deviations between theoretical and observed discharge, which provides a degree of robustness against random uncertainty. Although these uncertainties may affect specific numerical estimates, they have limited influence on the qualitative conclusions regarding the restructuring of hydrological regimes and their driving mechanisms.

Comment 5:

River-lake interaction is a highly complex hydraulic and hydrodynamic process. Although this study combines SWAT and LightGBM, the key inference still appears to rely heavily on a data-driven framework rather than on explicit hydraulic/hydrodynamic process representation. Therefore, the mechanistic interpretation is still not deep enough, and the credibility of some conclusions may be limited by the accuracy of the hydrological model. This limitation should be more clearly acknowledged and discussed.

We thank the reviewer for the insightful comments regarding the mechanistic aspects of the method. We agree that river–lake interactions are inherently governed by complex hydrodynamic processes and that, since no explicit hydrodynamic model is employed in this study, certain limitations exist in terms of mechanistic representation. Accordingly, additional discussion has been incorporated into the revised manuscript in order to more clearly define the applicability and limitations of the proposed approach.

It should be noted, however, that the primary objective of this study is not to explicitly simulate the coupled hydrodynamic processes of the river–lake system, but rather to identify the dominant controls on discharge at Hukou and to attribute its stage-dependent transitions from the perspective of basin forcing and lake response. In this context, the LightGBM model is used to represent the natural response of the lake system under weak mainstream interference, and is not intended to replace a physically based hydrodynamic model.

Although the approach is data-driven, the results exhibit clear physical consistency. For example, under strong backflow and backwater conditions, the reconstructed discharge under the assumption of no mainstream interference is significantly higher than the observed discharge, which corresponds to positive values of the BI index and reflects the suppression of outflow at Hukou. This behavior is consistent with the hydrodynamic mechanism whereby mainstream backwater inhibits lake outflow. Moreover, the identified deviations show pronounced temporal clustering and directional consistency, rather than random dispersion, which suggests that they primarily arise from systematic external hydrodynamic forcing rather than from model error.

From a methodological perspective, the approach can be understood as an observation-driven counterfactual framework, within which a reference state without strong mainstream interference is constructed, so that the deviation of the actual system from this baseline can be quantified, thereby allowing the indirect identification of the influence of mainstream hydrodynamic processes. In this sense, the method provides a feasible pathway for mechanism identification under conditions where detailed hydrodynamic modeling is not available.

At the same time, it is acknowledged that the present approach does not explicitly resolve key hydrodynamic variables such as water level, flow velocity, and hydraulic gradient, and therefore involves a degree of simplification in mechanistic representation. Future studies could integrate one- or two-dimensional hydrodynamic models, through which water level and discharge processes in the lake can be jointly simulated, in order to further improve the representation of river–lake interaction mechanisms.

The corresponding discussion has been added and refined in the revised manuscript Lines 513–519：

It should also be noted that river–lake interactions inherently involve coupled processes among water level, flow velocity, and hydraulic gradients. The present study focuses on system response characteristics and does not explicitly resolve detailed hydrodynamic processes. Future work could extend this framework by incorporating one-dimensional or two-dimensional hydrodynamic models, combined with cross-sectional data at Hukou and boundary conditions from the Yangtze River, to simulate coupled water level–discharge dynamics. In addition, integrating process-based models with data-driven approaches may enable a more comprehensive multi-scale characterization of river–lake interactions and further improve the mechanistic interpretation.

Comment 6:

An uncertainty analysis is needed. At minimum, the manuscript should discuss uncertainties associated with SWAT simulation, the LightGBM model, event classification thresholds, and the attribution procedure, and explain how these uncertainties may affect the quantitative estimates of dam impacts.

We thank the reviewer for the valuable suggestion. We agree that a systematic assessment of uncertainties associated with the models and attribution results is essential for strengthening the robustness of the study. In the revised manuscript, additional uncertainty analysis has been incorporated into Section 4.3, in which three aspects are discussed in a structured manner, including (1) uncertainties associated with the SWAT simulations, (2) uncertainties related to the LightGBM-based discharge response model at Hukou, and (3) uncertainties inherent in the attribution framework itself.

With respect to the SWAT model, it is acknowledged that the simulation accuracy varies among tributaries, which may introduce uncertainty in the magnitude of basin inflow. However, since the focus of this study is on the relative variations and stage-dependent characteristics of hydrological processes rather than on absolute values, the influence of this uncertainty on the main conclusions is considered to be limited.

Regarding the LightGBM model, it is further clarified that the model is developed under normal-flow conditions, when mainstream interference is relatively weak, and is subsequently applied to backflow and low-water scenarios, which may introduce a certain degree of extrapolation uncertainty. Nevertheless, given that the model demonstrates high accuracy under baseline conditions, with NSE values of approximately 0.94 and PBIAS close to zero, and that the identified deviations exhibit consistent directional behavior and physical plausibility in typical events, these deviations are more likely to reflect systematic hydrodynamic responses rather than random model errors.

For the attribution approach, it is emphasized that the analysis is conducted within a counterfactual framework, in which the influence of mainstream hydrodynamics is identified through the systematic deviation between reconstructed and observed discharge. By examining the structural characteristics of these deviations and their relationship with basin inflow, the method is able to reduce, to some extent, the influence of random errors on the interpretation of results.

Overall, it has been clarified in the revised manuscript that, although the aforementioned uncertainties may affect the exact numerical estimates, they do not alter the main conclusions regarding the reconstruction of river–lake hydrological interactions and their dominant driving mechanisms. The corresponding revisions can be found in Lines 489–512：

4.3 Limitations and Implications for Future Management

This study develops an integrated analytical framework that combines observational data, machine learning, and hydrological modeling to quantify the evolution of hydrological conditions in Poyang Lake under the influence of the Three Gorges Project. The approach can be regarded as an observation-driven counterfactual framework, in which a reference condition without mainstream interference is constructed to quantify deviations in the actual system, thereby indirectly identifying the influence of mainstream hydrodynamics. Based on this framework, a set of evaluation indicators is established to systematically analyze lake regulation mechanisms under different hydrological conditions from the perspectives of basin inflow and mainstream constraints. The discharge response model constructed under normal-flow conditions shows high accuracy under baseline conditions, and the deviations identified in typical events exhibit consistent directionality and physical plausibility, which indicates that the method is capable of capturing system responses and provides a feasible approach for mechanism identification under complex river–lake interaction conditions where high-resolution hydrodynamic boundary data are unavailable.

Despite these advantages, several sources of uncertainty should be acknowledged. First, basin inflow simulation is based on the SWAT model, and differences in simulation accuracy among tributaries may introduce uncertainty in the magnitude of inflow. However, since this study focuses on relative changes and stage-dependent characteristics, the influence of this uncertainty on the overall conclusions is limited. Second, the discharge response model is constructed based on normal-flow conditions, and its application to backflow and low-flow events may introduce some extrapolation error. Nevertheless, the model shows high accuracy under baseline conditions, and the identified deviations exhibit consistent directional behavior in typical events, which suggests that the results primarily reflect systematic responses rather than random error. In terms of attribution, the counterfactual framework identifies the influence of mainstream hydrodynamics through systematic deviations between theoretical and observed discharge, which provides a degree of robustness against random uncertainty. Although these uncertainties may affect specific numerical estimates, they have limited influence on the qualitative conclusions regarding the restructuring of hydrological regimes and their driving mechanisms.

Comment 7:

Overall, I think the topic is meaningful, but the current manuscript still needs clearer model description, stronger model evaluation, and a more cautious interpretation of the attribution results.

We sincerely thank the reviewer for the overall assessment and constructive suggestions. In response to the concerns regarding the clarity of model description, the adequacy of model evaluation, and the need for a more cautious interpretation of attribution results, we have carried out a series of systematic revisions in the manuscript.

Specifically, in the Methods section, the inputs and outputs of the SWAT and LightGBM models, as well as the linkage between them, have been further clarified, so that the modeling framework is explicitly presented as a sequentially connected approach rather than a fully coupled model. In terms of model evaluation, in addition to the original metrics, NSE, RMSE, and PBIAS have been incorporated to provide a more comprehensive assessment of model performance, and additional figures have been included to improve the robustness and transparency of the results. For the attribution analysis, the physical interpretation of the counterfactual framework has been further strengthened, and an expanded uncertainty analysis has been added in the Discussion section, through which the results are interpreted in a more cautious and comprehensive manner.

These revisions have been incorporated into Sections 2.4 and 4.3 of the revised manuscript. Once again, we sincerely appreciate the reviewer's valuable comments, which have significantly improved the clarity and rigor of this study.